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Impact of Natural Disasters on Income Inequality in Sri Lanka

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Abstract: We explore the relationship between natural disasters and income inequality in Sri Lanka as the first study of this nature for the country. The analysis uses a unique panel data set constructed for the purpose of this paper. It contains district inequality measures based on household income reported in six waves of the Household Income and Expenditure Survey of Sri Lanka during the period between 1990 and 2013, data on disaster affected population and other economic and social indicators. Employing a panel fixed effects estimator, we find that contemporaneous natural disasters and their immediate lags significantly and substantially decrease inequality in per adult equivalent household income as measured by the Theil index. Findings are robust across various inequality metrics, sub-samples and alternative estimators such as Ordinary Least Squares and System GMM. However, natural disasters do not affect household expenditure inequality. Either households behave as if they have a permanent income or all households reduce their expenditure proportionately irrespective of their income level in responding to natural disasters. Natural disasters decrease non-seasonal agricultural and non-agricultural income inequality but increase seasonal agricultural income inequality. Income of richer households is mainly derived from non-agricultural sources such as manufacturing and business activities and non-seasonal agricultural activities. Poorer households have a higher share of agricultural income.

Keywords: Natural disasters, economic impact, income inequality

JEL Classification: Q54, O11, O15

1. Introduction

Natural disasters disproportionally affect the poor. It is therefore often assumed that natural disasters increase income inequality. However, as Karim and Noy (2016) point out, there is little research on the impact of natural disasters on income inequality. This paper contributes with a study of Sri Lanka.

In the aftermath of a natural catastrophe, it is essential that affected agents should have access to timely and sufficient finances to ensure a smooth and speedy recovery (Keerthiratne & Tol, 2017). Wealthy individuals are in a better position to meet this financial requirement through self-financing as they can use their savings for reconstruction, they are more likely to have bought insurance to cover any losses, and they have better access to loans and credit. Not only that, the rich are often better prepared for natural disasters as they can financially afford to have precautionary solutions to avoid or mitigate disaster damages. Further, the poor are more likely to have irregular income, so that every disruption, either due to the disaster directly or dealing with the aftermath, means a loss in income. As such, even within the same country, natural disasters would differently affect rich and poor individuals. Natural disasters may thus negatively affect the level of income of the poor leading to a widened income inequality in society.

Furthermore, disaster affected territories generally suffer economic damages by way of human and physical capital losses which usually cause declines in average incomes. Accordingly, this may lead to spatial disparities in average incomes ultimately increasing income inequality among individuals within the same economy.

As Karim and Noy (2016, p. 4) highlight, it is apparent from the existing literature that "poorer households are more vulnerable and will bear the direct damages of disasters disproportionally at higher levels and as higher shares of their household's income" compared to rich households (Datt & Hoogeveen, 2003; Kim, 2012; Masozera, Bailey, & Kerchner, 2007; Morris et al., 2002; Rodríguez-Oreggia, 2010; Tesliuc & Lindert, 2002; Toya & Skidmore, 2007).

When a disaster strikes, the magnitude of its impact on an economy depends on characteristics of disaster itself and the prevailing conditions and socio-economic status of the affected territory as a whole. It appears that as a result of a similar natural disaster event more vulnerable poor countries suffer to a greater extent as opposed to their well-prepared wealthy counterparts. Quoting the World Bank, McDermott, Barry, and Tol (2014, p. 751) highlight that 97% of deaths related to natural disasters occur in developing countries and poor countries experience extremely high economic losses as a share of gross national product than rich countries due to natural disasters.

Whilst arguing that natural disasters cause human and economic losses irrespective of the level of economic development countries have achieved, Yamamura (2015) employs panel data for 86 countries covering the period from 1970 to 2004 to examine how the occurrence of natural disasters has affected the income inequality, as measured by Gini coefficient. He finds that natural disasters increase income inequality in the short run, however, this is not observable in the long run.

As Karim and Noy (2016, p. 4) suggest "the direct impact of disasters on the poor (in magnitude, and relative to the rich) cannot be answered" fully by merely "examining the cross-country distribution of costs and economic activity…the evidence on the distribution of the direct impact of a disaster within a country on households in various income levels is less well understood" as it clearly depends on country characteristics. As such, country level research is warranted in this field.

Using the Vietnam Household Living Standard Survey in 2008, Bui, Dungey, Nguyen, and Pham (2014) find that natural disasters increased income inequality among households in Vietnam in 2008. When natural disasters occur, households can suffer large losses in assets and income. However, poor may be more vulnerable to loss of income due to their inability to engage in work and the unavoidable sale of income deriving capital assets as a coping strategy. If poorer households are less prepared for disasters; the poor lives in disaster prone areas and homes that are more likely to be damaged; and receives earnings mainly from sectors which are more likely to face downturn (e.g., weather dependent traditional agriculture), poor would bear higher income losses and natural disasters could cause greater income inequality.

Investigating the impact of Cyclone Aila in Sundarbans region in Bangladesh in 2009, Abdullah, Zander, Myers, Stacey, and Garnett (2016) establish that income inequality decreased after the Cyclone. Another very recent paper by Feng, Lu, Nolen, and Wang (2016) show that household income fell by 14 % due to 2008 Sichuan earthquake in China, however, income inequality did not change. These findings may be somewhat surprising on the face of it as one would expect natural disasters to exacerbate income inequality.

At subsistence level, people possess little that can be lost to a natural disaster. Losses for the wealthier groups would be disproportionately greater due to natural disasters. People on a monthly wage would not see their income affected by a disaster, but small business owners would. Unskilled day labourers may find new opportunities in the reconstruction effort. In other words, the impact of natural disasters on income inequality is ambiguous.

Against this background, we study the impact of natural disasters on income inequality in Sri Lanka at district level, as the first study of this nature. We find that natural disasters decrease income inequality among Sri Lankan households in line with the results of the aforesaid two studies on Bangladesh and China. Our data allow us to decompose income sources, so that we better understand the mechanisms.

The paper proceeds as follows. Section 2 describes data and empirical strategy. Results are discussed in Section 3 followed by Section 4 which contains robustness checks. Section 5 sets out concluding remarks with some policy implications and also recognises the limitations of the study.

2. Empirical Analysis

2.1 Data

Sri Lanka is a lower middle income country. Officially known as the Democratic Socialist Republic of Sri Lanka, it is an island situated in the Indian Ocean just above the equator, bordering a major maritime route, the renowned 'Silk Route' connecting the western and eastern worlds. Sri Lanka is 65,610 km^2 in extent with a population of around 21.2 million. Sri Lanka is divided into 25 administrative districts within 9 provinces. As reported in the latest Annual Report of the (Central Bank of Sri Lanka, 2016), life expectancy of Sri Lankans is 75 years and they have a higher literacy rate of around 93%. Sri Lanka is ranked 73rd among 188 countries in the Human Development Index. In 2016, Sri Lanka recorded a gross domestic product (GDP) of US$ 81.3 billion and per capita income of US$ 3,835 (at current market prices). In Sri Lanka both unemployment and real growth rates were 4.4%, in 2016. After ending a 30 year long war and terrorism in 2009, the economy of Sri Lanka grew at an average rate of 6.4% during the next five years. Over the years Sri Lanka has developed to a service oriented economy from a traditional agricultural economy. In 2016, 62.5% of GDP was yielded from services sector, whilst manufacturing and agricultural sectors accounted for 29.6% and 7.9 of GDP, respectively.

Natural disaster data are from the Disaster Management Centre of Sri Lanka, which maintains disaster related data in collaboration with 'DesInventar', the Disaster Information Management System of UNISDR, United Nations Office for Disaster Risk Reduction. Income data and other social and economic indicators are obtained from the Household Income and Expenditure Survey (HIES) series conducted by the Department of Census and Statistics of Sri Lanka from 1990 to 2013. There are six waves, i.e. 1990/91, 1995/96, 2002, 2006/07, 2009/10 and 2012/13 where the data are representative at district level. The only wave which covers the entire country is the latest 2012/13 survey. Due to the ongoing civil war at that time, some districts of Northern and Eastern provinces were not covered in earlier waves. Mid-year district population data are taken from the Registrar General's Department of Sri Lanka and the study uses the Consumer Price Index published by the Central Bank of Sri Lanka.

Extracting the data reported in the official website of Disaster Management Centre, we construct a district-wise annual disaster database for Sri Lanka from 1985 – 2013. It contains the number of people affected due to cyclones, droughts, epidemics, floods, gales, heavy rains, landslides, land subsidence, plagues, storms, strong winds, surges, tornados, and tsunami in each district, yearly. According to the database, around 27 million people were affected from natural disasters in Sri Lanka during the period from 1985 to 2013. Of them, 47% and 45% were affected by droughts and floods, respectively. Extreme wind events were responsible for 6% of the population affected whilst 2% were affected due to epidemics. Following Noy (2009), we normalise the number affected by disasters with *lagged* population. Thus, disasters are measured as the percentage of population affected due to all natural disasters in each district during a calendar year.

To explore the impact of natural disasters on income inequality at district level in Sri Lanka, we compute the monthly income of each household in the survey year based on survey data of HIES series. In the calculations, we take into consideration all monetary and non-monetary income derived from all sources. Free State services, such as education and health, the value of which cannot be ascertained easily and exactly, were not included in the income. Accordingly, household income consists of the followings components (Department of Census and Statistics, 2015).

a) Employment income – wages-salaries, allowances (tips, commissions, overtime), bonus and arrears
b) Seasonal agricultural income – paddy, chillies, onions, vegetables, cereals, yams, tobacco
c) Other agricultural income – tea, rubber, coconut, coffee, pepper, betel, banana, fruits, meat, fish, egg, milk, other food, horticulture
d) Non-agricultural income – mining and quarrying, manufacturing, construction, trade, transport, guest house, restaurants, bars, hotels, etc.
e) Cash receipts – such as pensions, disability / relief payments, dividends, rents, interest amounts received from various types of savings, educational grants and scholarships, school food program, current remittances and local and foreign transfers, other income
f) Windfall income – income by chance or *ad hoc* gains such as compensations, lottery wins, loans, sale of assets such as land, house and jewellery, withdrawals from savings and bank deposits, gratuity, provident fund, income receives from births, deaths and marriages, receipts from welfare society, *seettu* (an informal savings scheme among households), repayments of loans given, health and medical aid, insurance, foods and other commendations, disaster relief assistance, etc.

g) Food in kind (mostly the estimated values of the household consumed items such as home grown fruits and vegetables)
h) Non-food in kind (includes estimated rental values of owner occupied housing units)

Household monthly income is calculated by aggregating monthly earnings received from all the components and then it is equivalised to take account of differences in household size and composition so that it becomes a representative income. To adjust incomes on the basis of household size and composition, all incomes are expressed as the amount that an adult would require to enjoy the same standard of living. We employ the widely used Organisation for Economic Co-operation and Development (OECD) modified equivalence scale for this purpose. This scale, first proposed by Hagenaars, De Vos, and Asghar Zaidi (1994), assigns a value of 1 to the household head, of 0.5 to each additional adult member and of 0.3 to each child. A caveat is that OECD modified scale takes into account only the age and number of members in a household even though there may be other characteristics which may vary from household to household such as disability or health status of household members that affect the needs and capacities of such households.

Adjusted household monthly income per adult equivalent after accounting for sample weights is used to calculate mean and median household incomes and inequality measures such as Theil index, Gini coefficient, inter quartile range and inter quintile range for average income for each district for each survey year. Income measures are converted to real terms using Colombo Consumers' Price Index (annual average, base year 2006/07) for comparison across survey years.

From the HIES 2006/07 onwards, 7 new sections have been introduced to the HIES series to collect almost all other household information that helps to understand the living standards of the households. These new areas are school education, health information, inventory of durable goods, access to infrastructure facilities, household debts and borrowings, information on housing, sanitary and disasters, and land and agriculture holdings (Department of Census and Statistics, 2015, p. 1).

Based on the above, we construct panel dataset for 25 administrative districts in Sri Lanka for six survey time periods which contains data on household incomes and expenditures, income and expenditure inequalities, natural disasters, etc. This is an unbalanced panel as the number of districts covered varies between 17 and 25. The only wave which covers the entire country is the latest 2012/13 survey. Due to the ongoing civil war at that time some districts of Northern and Eastern provinces were not covered in other waves.

Table 1: Summary statistics

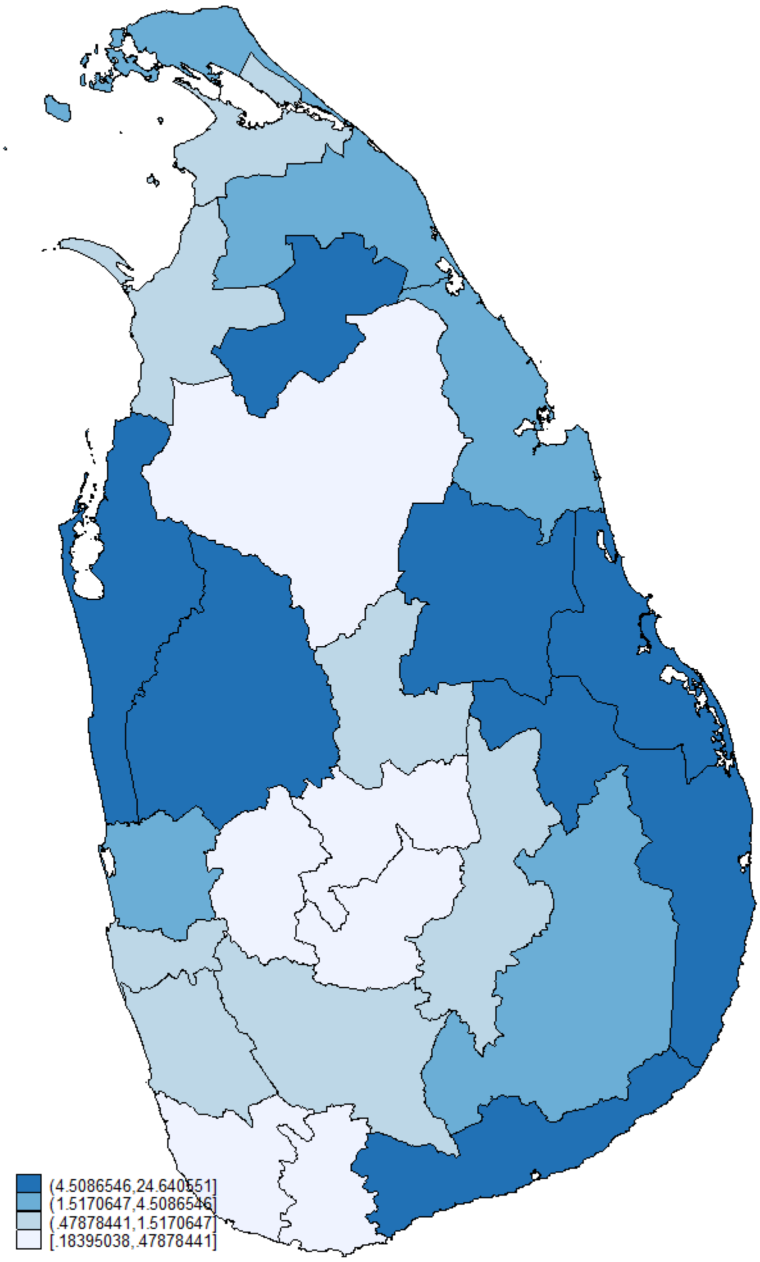
Variable	Obs	Mean	Std. Dev.	Min	Max
Theil	117	0.4396	0.3027	0.1675	2.4802
Gini	117	0.4276	0.0614	0.2880	0.7168
Inter Quartile Range (Rs.)	117	5,698	2,108	2,457	12,458
Inter Quintile Range, Avg. Income (Rs.)	117	20,688	10,433	8,383	74,676
Mean Household Income (Rs.)	117	8,891	3,388	4,404	20,580
Median Household Income (Rs.)	117	6,228	1,926	3,302	13,409
q1 Average Income (Rs.)	117	2,075	1,463	- 9,823	5,627
q2 Average Income (Rs.)	117	4,490	1,386	2,223	9,809
q3 Average Income (Rs.)	117	6,264	1,945	3,326	13,534
q4 Average Income (Rs.)	117	8,941	2,951	4,552	19,437
q5 Average Income (Rs.)	117	22,763	10,929	10,109	77,315
HCI (Head Count Index)	117	19.00	11.56	1.40	56.20
% of Poor Households	100	15.48	11.05	1.10	42.20
Household Size	117	4.23	0.38	3.68	5.13
% of HH without Electrical Items	66	38.17	15.37	4.70	90.60
% of HH without Vehicles	66	38.07	22.20	10.50	90.80
% of HH with No Rooms	65	2.20	1.87	0	9.00
% of HH with No Safe Drinking Water	66	13.17	10.93	0.50	48.60
% of HH with No Toilet	62	4.31	5.02	0.10	24.40
Disaster (% of Population Affected)	150	4.7368	13.4126	0	117.6589
Disaster_lag1	150	8.5613	22.1317	0	174.3878
Disaster_lag2	150	11.7633	23.4198	0	128.5260
Disaster_lag3	150	4.0579	8.0361	0	56.1630
Disaster_lag4	149	4.8619	10.9804	0	62.4662
Disaster_lag5	149	10.7272	24.9794	0	174.3878
Biological (% Population Affected)	150	0.1079	0.2629	0	3.1072
Climatic (% Population Affected)	150	2.2285	11.4782	0	117.5446
Geophysical (% Population Affected)	150	0.0137	0.1240	0	1.4415
Hydrological (% Population Affected)	150	2.1009	6.5334	0	52.6214
Meteorological (% Population Affected)	150	0.2859	2.9010	0	35.5536

Summary statistics for the variables used in the analysis are provided in Table 1. On average, disasters affect 5% of the population in a district per annum in Sri Lanka and the maximum percentage of population affected by natural disasters in a district can be as high as 118% (due to multiple disasters in a year). District-wise income inequality measured by Theil index is around 0.44 whilst Gini co-efficient is around 0.43. Per adult equivalent real mean household income is Rs. 8,891. It is also observed that the income of the richest quintile is more than 10 folds larger compared to the poorest quintile. Average household size is around 4 and about

15% of the households are poor. Around 2% of housing units are basic with no rooms. Around 38% of households do not possess vehicles or electric equipment. Meanwhile, around 13% of households do not have access to safe drinking water and around 4% of households do not have an exclusive toilet.

Figures 1 and 2 demonstrate the variation of mean inequality measured by Theil index and mean percentage of population affected due to natural disasters across districts in Sri Lanka[1].

Figure 1: Variation of mean percentage of population affected due to natural disasters



[1] We used the Stata command spmap by Maurizio Pisati. See https://ideas.repec.org/c/boc/bocode/s456812.html

Figure 2: Variation of mean inequality measured by Theil index across districts

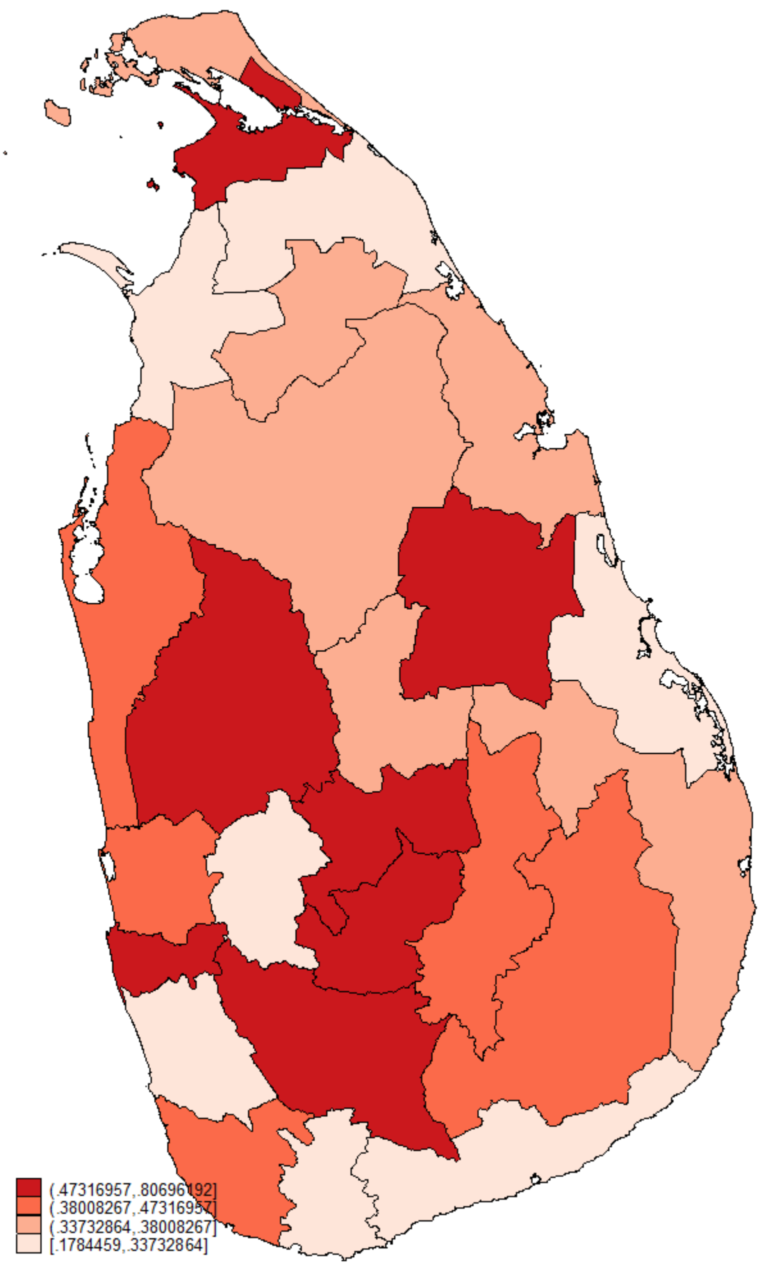
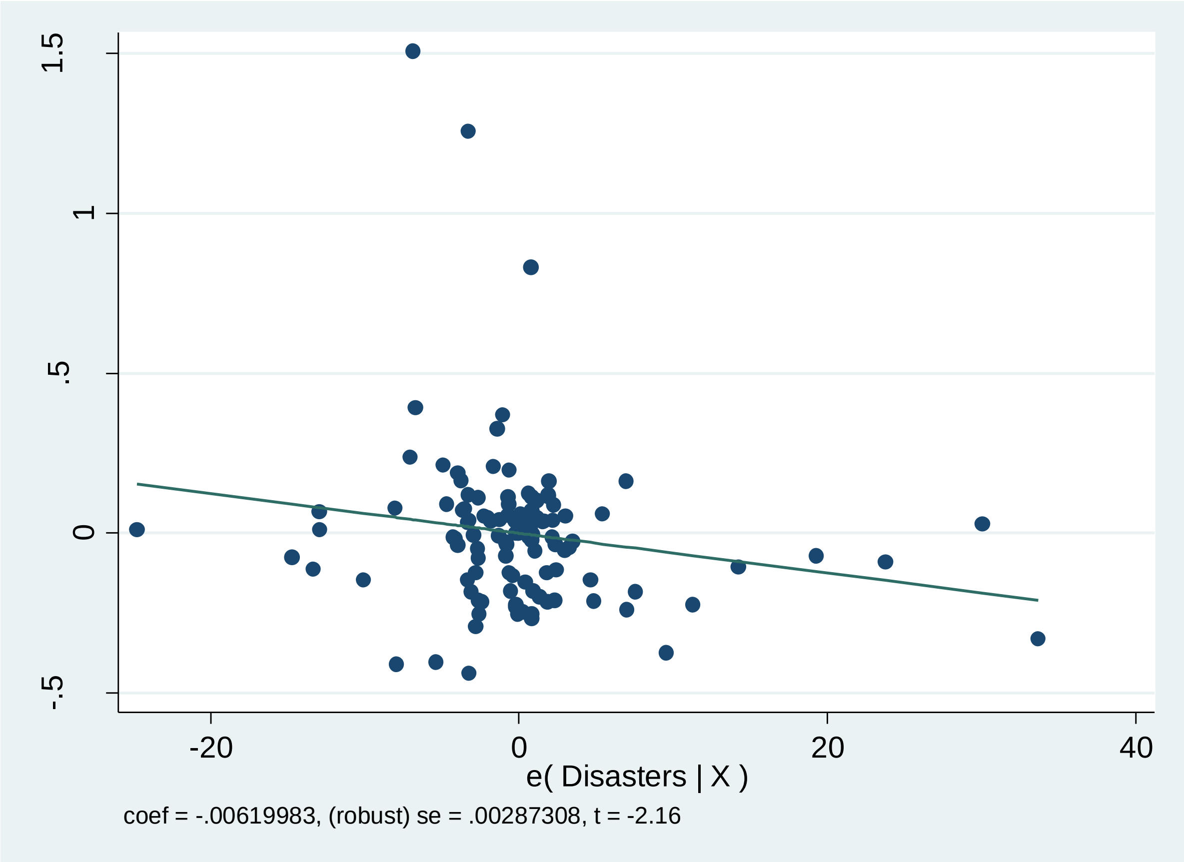


Figure 3 depicts the relationship between current natural disaster affected population (%) and income inequality measured by Theil index after controlling for disaster lags, time invariant district fixed effects and time fixed effects. There appears to be a significant negative correlation between disasters and income inequality suggesting a possible reduction of income inequality by natural disasters.

Figure 3: Association between Theil index and natural disasters



Notes: Above graphical representation is obtained using avplot command in Stata/IC 14.1 after controlling for disaster lags, district and time fixed effects.

2.2 Empirical Model

We employ a panel regression estimator with district and time fixed effects as the main estimation strategy in our analysis. Fixed effects estimator is chosen since district and time fixed effects control for time-invariant spatial heterogeneity among districts and time-variant shocks that simultaneously affect all the districts, respectively. As such, this approach reduces any potential endogeneity issue.

The panel regression equation of the baseline model is as follows;

$$Inequality_{it} = \alpha_i + \beta_t + \gamma\ Dis_{it} + \Gamma Dis_{i\ t-n} + \varepsilon_{it} \quad (1)$$

where income inequality as measured by Theil index in district *i* in Sri Lanka for survey time *t* is the dependent variable. *Dis* is our variable of interest, disaster impact measured as the percentage of population affected due to all natural disasters occurred during the survey year in each district. We also include lagged disasters in the regression. Given the data availability, for each survey time five disaster lags are included in the regression in addition to the current disaster variable. Terms α_i and β_t are the district and time fixed effects included in the model, respectively. The final term ε_{it} in the equation is the error term. Errors are clustered at district level.

We check against omitted variable bias by adding more control variables, such as median household income, headcount index, % of poor households and other indicators which reflect social and economic status of households. In addition to the Theil index, we employ other alternative inequality measures such as the Gini coefficient, inter quartile range and inter quintile range of average income as the dependent variable. We rerun regressions excluding the extreme survey waves, i.e., 2006/07 which was after 2004 tsunami and 2009/10 survey which was after the ending of war/terrorism, to ensure that results are not driven by these extreme waves.

Apart from the panel fixed effect estimator we use alternative estimators such as ordinary least squares (OLS) and System GMM to support our findings; see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), (Roodman, 2009a) and (Roodman, 2009b). Once we are convinced that natural disasters affect income inequality, we explore how natural disasters affect level of income itself, particularly in different quintiles. As it is evident that income of all quintiles is reduced in the presence of disasters we decompose inequality measured by Theil index into income components and compare results with the differences in income composition of poor and rich quintiles which explains findings. As we are using the household income and expenditure survey data, we investigate whether there is any relationship between household expenditure inequality and natural disasters. We expand our analysis to disaster subgroups and finally repeat our analyses excluding biological disasters as the mechanisms are so different.

3. Results

3.1 Base Model

Results of the baseline model are given in Table 2. We find statistically significant negative impact of natural disasters that occurred in the same year, two years and three years prior to the survey on income inequality measured by Theil index. However, there appear to be a significant positive impact of natural disasters that took place 4 years before the survey on income inequality. Accordingly, an increase of current disaster affected population by one percentage point would reduce income inequality measured by Theil index by 0.0062 points, *ceteris paribus*.

As this interpretation may suffer from lack of immediate apprehension, we provide here a hypothetical illustration for clarity. Using the latest 2012/13 Survey data, national inequality measured by Theil index is 0.46008. If we deduct the income of each household in the 5th quintile by 0.483% and redistribute the proceeds equally among all households in the poorest quintile, the resultant Theil is 0.45388 (i.e. 0.46008 - 0.0062). Thus, an increase in disasters to affect one extra percentage point of people is equivalent to a half percent income tax on the richest fifth for redistribution to the poorest fifth.

Table 2: Results for regressing income inequality on natural disasters: Base model

	Dependent variable: Income inequality (Theil)
	Fixed Effects
Disaster (% Population Affected)	-0.00620**
	(0.00252)
Disaster_lag1	0.000640
	(0.00106)
Disaster_lag2	-0.00338*
	(0.00166)
Disaster_lag3	-0.00414*
	(0.00208)
Disaster_lag4	0.00473**
	(0.00225)
Disaster_lag5	0.000189
	(0.00144)
Observations	117
Number of Districts	25
R-squared	0.186

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

In our regressions we cluster errors at district level. Since administrative policy implementation is mostly carried out at provincial level, we alternatively clustered at provincial level also considering the potential spatial correlation of natural disasters and found similar results.

3.2 Disaster impact on inequality of components of income

To disentangle the ways by which income inequality is decreased due to natural disasters, we decompose income into its components, and compute the Theil index for each component. Tables 3 and 4 reveal that the negative impact of natural disasters on income inequality is not driven by receipts (which include any disaster relief payments) or by any foreign or domestic remittances households receive after disasters. Natural disasters and their immediate lags significantly decrease non-agricultural income inequality and non-seasonal agricultural income inequality, but increase seasonal agricultural income inequality. Given the strict labour laws which ensure the rights of employees in formal employment, Sri Lanka does not see any effect of natural disasters on employment income inequality.

Table A.1 in the Appendix and Table 5 show the composition of household income varies across quintiles. Rich quintiles receive a higher share of their income from non-agricultural sources such as business activities and non-seasonal agricultural activities compared to the poor whilst the share of income the poor receives from these sources is much lower. Further, poorest households earn a higher share of income from seasonal agriculture most probably weather dependent, compared to the richest quintile.

Table 3: Results for regressing income inequality on natural disasters, by income component

	Dependent variable: Inequality – Component of income (Theil)							
	(1) Total	(2) Employ	(3) Agri	(4) Agri_Other	(5) Non_Agri	(6) Kind	(7) Receipts	(8) Remittances
Disaster	-0.00620**	0.000707	0.00200*	-0.00961**	-0.0112**	-0.00272	9.03e-05	0.00313
	(0.00252)	(0.000639)	(0.00117)	(0.00396)	(0.00525)	(0.00160)	(0.00155)	(0.00212)
Dis_lag1	0.000640	0.000133	-0.00100	0.00326	-0.000655	-0.000824	0.000355	0.000733
	(0.00106)	(0.000256)	(0.000695)	(0.00249)	(0.00146)	(0.000648)	(0.000630)	(0.000832)
Dis_lag2	-0.00338*	-0.000314	0.00209**	-0.00181	-0.00592**	0.000620	-0.00134	0.00183*
	(0.00166)	(0.000495)	(0.000884)	(0.00238)	(0.00248)	(0.000758)	(0.000907)	(0.000997)
Dis_lag3	-0.00414*	-0.000763	-0.00260	-0.0127***	-0.00525	-6.12e-05	0.000392	-0.000528
	(0.00208)	(0.000636)	(0.00287)	(0.00431)	(0.00569)	(0.00190)	(0.00150)	(0.00230)
Dis_lag4	0.00473**	-0.000156	0.00221	0.00513	0.0128**	-0.000331	0.00398**	-0.00101
	(0.00225)	(0.000623)	(0.00156)	(0.00515)	(0.00530)	(0.00148)	(0.00147)	(0.00164)
Dis_lag5	0.000189	0.000207	-0.000370	0.00153	0.000430	-0.00102	0.000755*	0.000590
	(0.00144)	(0.000244)	(0.000491)	(0.00200)	(0.00352)	(0.000682)	(0.000419)	(0.000611)
Observations	117	117	117	117	117	117	117	117
R-squared	0.186	0.114	0.244	0.251	0.112	0.510	0.515	0.156
Districts	25	25	25	25	25	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Summary: How do disasters affect inequality of components of income?

	Dependent variable: Inequality – Component of income (Theil)						
	(1) Total Income	(2) Employ	(3) Agri	(4) Agri_Other	(5) Non_Agri	(6) Kind	(7) Receipts
Disasters	↓		↑	↓	↓		
Dis_lag1							
Dis_lag2	↓		↑		↓		
Dis_lag3	↓			↓			
Dis_lag4	↑				↑		↑
Dis_lag5							↑

Table 5: Average share of income by components (%)

	Employ	Agri	Agri_other	Non_agri	Kind	Receipts
Q1	44.22	7.01	4.98	1.43	22.63	19.80
Q2	47.18	5.40	6.69	9.72	15.86	15.07
Q3	48.06	5.13	7.36	9.58	14.60	15.27
Q4	44.21	4.82	7.69	12.73	14.10	16.44
Q5	31.29	3.32	11.83	24.48	11.53	17.43
Disaster Impact			↓	↓	↓	

4. Robustness Checks

4.1 Additional Controls

The above results hold in the presence of other control variables, namely, real median household income, poverty head count index (HCI) and the share of poor households (Table 6). The HCI is the percentage of population below the official poverty line, which is based upon the real total expenditure per person per month; a household with members whose per capita expenditure is below the official poverty line is considered as a poor household (Department of Census and Statistics, 2015).

Table 6: Results for regressing income inequality on natural disasters: Controls

	Dependent variable: Income inequality (Theil)	
	(1)	(2)
Disaster (% Population Affected)	-0.00805***	-0.00947***
	(0.00224)	(0.00300)
Disaster_lag1	-0.000313	-0.000435
	(0.00134)	(0.00165)
Disaster_lag2	-0.00308**	-0.00404
	(0.00134)	(0.00249)
Disaster_lag3	-0.00585**	-0.00831*
	(0.00268)	(0.00450)
Disaster_lag4	0.00650**	0.00504
	(0.00260)	(0.00311)
Disaster_lag5	0.000152	9.85e-06
	(0.00132)	(0.00113)
Real Median HH Income (logged)	0.0986	-0.0799
	(0.237)	(0.281)
HCI	0.0190*	
	(0.00950)	
% of Poor HH		0.0174
		(0.0113)
Observations	117	100
R-squared	0.245	0.203
Number of Districts	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2 Alternative inequality metrics

We check whether our results hold for different inequality measures such as Gini coefficient, inter quintile range for average income and inter quartile range. As shown in Table 7, disasters and their immediate lags reduce income inequality not only measured by the Theil index but also by the Gini coefficient and the inter quintile range of average income. Further, disasters occurred in the previous year seem to significantly reduce inter quartile range of income.

Table 7: Results for regressing income inequality on natural disasters: Alternative inequality metrics, Gini coefficient, inter quintile range (IQ^5R), and inter quartile range (IQ^4R)

	Dependent variable: Income inequality		
	(1)	(2)	(3)
	Gini	IQ^5R (ln)	IQ^4R (ln)
Disaster (% Pop. Affected)	-0.00139***	-0.00453***	0.000759
	(0.000396)	(0.00126)	(0.000718)
Disaster_lag1	-3.73e-05	-0.000605	-0.000764**
	(0.000242)	(0.000991)	(0.000279)
Disaster_lag2	-0.000596**	-0.00235**	-0.000268
	(0.000227)	(0.000948)	(0.000593)
Disaster_lag3	-0.00128**	-0.00557**	-0.000123
	(0.000531)	(0.00210)	(0.000646)
Disaster_lag4	0.00156**	0.00627**	0.000621
	(0.000646)	(0.00275)	(0.00184)
Disaster_lag5	2.73e-05	-0.000245	4.59e-05
	(0.000214)	(0.000830)	(0.000378)
Real Median HH Income (logged)	-0.0584	0.570*	0.629**
	(0.0490)	(0.285)	(0.230)
HCI	0.00252	0.00512	-0.00391
	(0.00152)	(0.00850)	(0.00312)
Observations	117	117	117
R-squared	0.411	0.808	0.945
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Results for regressing income inequality on natural disasters: Current disasters with additional controls

	Dependent variable: Income inequality		
	(1)	(2)	(3)
	Theil	Gini	Inter Quin. Range (ln)
Disaster (% Pop. Affected)	-0.0151***	-0.00209***	-0.00912***
	(0.00492)	(0.000736)	(0.00243)
% of HH without safe drinking water	0.0140*	0.00219*	0.00483
	(0.00757)	(0.00122)	(0.00502)
% of HH without a toilet	-0.0161	-0.00364	-0.0207
	(0.0310)	(0.00529)	(0.0199)
% of HH with no rooms	-0.0532	-0.00588	0.0117
	(0.0513)	(0.00909)	(0.0345)
% of HH without electric equipment	0.0210	0.00124	-0.000979
	(0.0128)	(0.00203)	(0.00825)
% of HH without vehicles	-0.00183	0.00136	-0.00370
	(0.0120)	(0.00198)	(0.00772)
Observations	61	61	61
R-squared	0.232	0.202	0.177
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

When we run the regression for alternative inequality measures with current disasters only and additional relevant controls on access to safe drinking water and hygienic facilities, structure of the house and possession of movable properties which reflect socio-economic status of households, we observe that current disasters significantly decrease income inequality measured by alternative inequality metrics (Table 8).

4.3 Outliers

We exclude the survey wave 2006/07 which was after the Indian Ocean tsunami in December 2004 and the survey wave 2009/10 which was after the ending of 30 years long terrorist war alternatively and simultaneously, results still remain significant (Table 9).

Table 9: Results for regressing income inequality on natural disasters: Excluding possible outlier waves

	Dependent variable: Income inequality (Theil)		
	(1) Without wave just after Tsunami	(2) Without wave after ending of war	(3) Without both waves
Disaster (% Pop. Affected)	-0.00541**	-0.00399*	-0.00116*
	(0.00260)	(0.00230)	(0.000617)
Disaster_lag1	0.000326	0.00104	0.000493
	(0.00105)	(0.00115)	(0.000786)
Disaster_lag2	-0.00174*	-0.00260	0.000246
	(0.000921)	(0.00174)	(0.00144)
Disaster_lag3	-0.00229	-0.00416**	-0.00750**
	(0.00350)	(0.00169)	(0.00298)
Disaster_lag4	0.00504**	0.00298	-2.12e-05
	(0.00200)	(0.00184)	(0.00325)
Disaster_lag5	0.00226	-0.000598	-0.000578
	(0.00406)	(0.00107)	(0.00116)
Observations	98	95	76
R-squared	0.228	0.212	0.367
Number of Districts	25	25	25

Notes: Panel of district level inequality measures for five waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4 Alternative Estimators

As a further robustness check, we re-estimate the model using ordinary least squares (OLS) and, difference and system generalised method of moments (GMM) estimators. As apparent from Table 10, alternative estimators, OLS and system GMM yield consistent results.

Difference GMM also yields consistent results at least with respect to the sign on the coefficient. In this exercise, we restrict our explanatory variables to current disasters and HCI. The GMM uses lagged values of independent variables which are not strictly exogenous as internal instruments. Therefore, the inclusion of additional disaster lags in the model may complicate the process.

Table 10: Results for regressing income inequality on natural disasters: Alternative estimators

	Dependent variable: Income inequality (Theil)			
	(1)	(2)	(3)	(4)
	FE	OLS	Diff. GMM	Sys. GMM
Disaster (% Pop. Affected)	-0.00621**	-0.00362**	-0.00509	-0.00821**
	(0.00275)	(0.00152)	(0.00363)	(0.00363)
HCI	0.0147	0.00284	0.0166	0.0182
	(0.00910)	(0.00361)	(0.0128)	(0.0146)
Observations	117	117	92	117
R-squared	0.198	0.115		
Number of Districts	25		22	25
Number of Instruments			10	11
Arellano-Bond Test AR(1)			0.067	0.088
Arellano-Bond Test AR(2)			0.714	0.652
Hansen Test			0.234	0.213

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Lags used to instrument the endogenous variables in system GMM regression limited to 10.

4.5 Disaster impact on income

As shown in Table 11, current natural disasters negatively affect mean household income whilst the disasters occurred in the previous year negatively affect median household income. Income of the poorest quintile is reduced by current disasters and disasters occurred three years before. Income of the middle quintiles is reduced by the disasters occurred in the previous year. Richest quintile's income is decreased by current disasters and disasters occurred two and three years before. So, we find clear evidence that income of all the quintiles is affected by natural disasters.

Table 11: Results for regressing income on natural disasters

	Dependent variable: Household income (logged)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean	Median	q1	q2	q3	q4	q5
Disasters	-0.00507**	-0.00180	-0.0109***	-0.00212	-0.00172	-0.00152	-0.00613***
	(0.00185)	(0.00154)	(0.00387)	(0.00159)	(0.00163)	(0.00166)	(0.00186)
Dis_lag1	-0.000724	-0.00101***	0.00151	-0.00102***	-0.00108***	-0.00127***	-0.000596
	(0.000537)	(0.000299)	(0.00205)	(0.000331)	(0.000292)	(0.000301)	(0.000832)
Dis_lag2	-0.00104	0.000328	0.00104	0.000502	0.000298	0.000107	-0.00209**
	(0.000691)	(0.000561)	(0.00127)	(0.000763)	(0.000567)	(0.000475)	(0.000945)
Dis_lag3	-0.00358*	-0.00124	-0.00598*	-0.00111	-0.000954	-0.000852	-0.00546**
	(0.00192)	(0.00141)	(0.00304)	(0.00174)	(0.00142)	(0.00134)	(0.00239)
Dis_lag4	0.00209	0.000165	0.00269	-5.09e-05	0.000146	0.000795	0.00485*
	(0.00157)	(0.00117)	(0.00263)	(0.00112)	(0.00113)	(0.00133)	(0.00235)
Dis_lag5	0.000563	0.000395	0.00180	0.000293	0.000355	0.000348	0.000333
	(0.000797)	(0.000424)	(0.00114)	(0.000473)	(0.000437)	(0.000508)	(0.000967)
Observations	117	117	113	117	117	117	117
R-squared	0.852	0.905	0.414	0.882	0.907	0.922	0.799
Districts	25	25	24	25	25	25	25

Notes: Panel of district level measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.6 Disasters and household expenditure inequality

We repeat our analysis for household expenditure inequality. As in the previous analysis, we calculate per adult equivalent household expenditure and then calculate district wise inequality measures for each survey wave. When we estimate our baseline specification using panel fixed effects estimator, we do not find any impact of natural disasters on expenditure inequality measured either by Theil index or Gini coefficient (Table 12). There may be two plausible explanations for this. One is that households suffer income losses due to natural disasters disproportionately across quintiles, however, they act as if they have a permanent income when it comes to expenditure and therefore do not change their spending behaviour. The other is that all the households reduce their expenditure proportionately across quintiles in the presence of natural disasters. Both scenarios would lead to no change in expenditure inequality among households due to natural disasters.

Table 12: Results for regressing expenditure inequality on natural disasters

	Dependent variable: Expenditure inequality	
	(1)	(2)
	Theil	Gini
Disaster (% Population Affected)	0.00116	0.000239
	(0.00145)	(0.000318)
Disaster_lag1	0.000136	4.41e-05
	(0.000130)	(8.06e-05)
Disaster_lag2	0.000427	0.000205
	(0.000321)	(0.000146)
Disaster_lag3	-5.63e-05	-5.06e-05
	(0.000434)	(0.000255)
Disaster_lag4	-0.00124	-0.000379
	(0.00131)	(0.000578)
Disaster_lag5	6.81e-05	6.54e-05
	(0.000172)	(6.67e-05)
Observations	117	117
R-squared	0.321	0.514
Number of Districts	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.7 Disaster Sub-Groups and income inequality

Accepting the fact that natural disasters differ in nature, intensity, duration and impact, we repeat our analysis by disaster sub-group. Table 13 shows a significant negative impact of geophysical, hydrological and meteorological disasters on different income inequality measures.

Table 13: Results for regressing income inequality on natural disasters by disaster type

	Dependent variable: Income inequality			
	(1)	(2)	(3)	(4)
	Theil	Gini	IQR (ln)	Inter Quin. Range (ln)
Biological	0.0645	0.00520	0.0447*	0.0157
	(0.146)	(0.0198)	(0.0238)	(0.0782)
Climatic	-0.00411	-0.000545	0.000362	-0.00149
	(0.00328)	(0.000485)	(0.00144)	(0.00128)
Geophysical	-0.181*	-0.0587***	-0.0250	-0.185***
	(0.0879)	(0.0144)	(0.0201)	(0.0558)
Hydrological	-0.00729	-0.00123	-0.00261	-0.00875**
	(0.00574)	(0.00135)	(0.00246)	(0.00398)
Meteorological	-0.00102	-5.91e-05	-0.00760***	-0.0115***
	(0.00443)	(0.00100)	(0.00153)	(0.00227)
Observations	117	117	117	117
R-squared	0.164	0.333	0.902	0.786
Number of Districts	25	25	25	25

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Some argue that biological disasters are very different from other natural disasters. We therefore replicate the analysis excluding biological disasters from total disasters. This exercise derives similar results as for the base model (see Table 14).

Table 14: Disasters excluding biological disasters and income inequality

	Dependent variable: Income inequality (Theil)
	Fixed Effects
Disaster (% Population Affected)	-0.00624**
	(0.00256)
Disaster_lag1	0.000627
	(0.00106)
Disaster_lag2	-0.00341*
	(0.00167)
Disaster_lag3	-0.00421*
	(0.00209)
Disaster_lag4	0.00465*
	(0.00226)
Disaster_lag5	0.000184
	(0.00144)
Observations	117
Number of Districts	25
R-squared	0.186

Notes: Panel of district level inequality measures for six waves of surveys with corresponding contemporaneous and lagged disaster data. Model includes a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses.

As shown in Table 15, different natural disaster sub-groups affect mean, median household incomes and income across quintiles differently.

Table 15: Different disaster sub-groups and income

	Dependent variable: Household Income (logged)						
	(1)	(2)	(3)	(4)	(5)	(5)	(7)
	Mean	Median	q1	q2	q3	q4	q5
Biological	0.0443	0.0398***	-0.0268	0.0300***	0.0360***	0.0276*	0.0283
	(0.0599)	(0.0117)	(0.0374)	(0.00981)	(0.0111)	(0.0140)	(0.0805)
Climatic	-0.00368*	-0.00117	-0.0111**	-0.00141	-0.00101	-0.000659	-0.00347
	(0.00213)	(0.00124)	(0.00478)	(0.00111)	(0.00128)	(0.00131)	(0.00207)
Geophysical	-0.110***	0.0361*	-0.430***	0.0227	0.0339*	0.0152	-0.202***
	(0.0318)	(0.0188)	(0.0601)	(0.0182)	(0.0187)	(0.0178)	(0.0516)
Hydrological	-0.00587***	-0.00287	-0.00595	-0.00350	-0.00317	-0.00320	-0.00826**
	(0.00184)	(0.00232)	(0.00424)	(0.00236)	(0.00240)	(0.00234)	(0.00371)
Meteorological	-0.0118***	-0.00962***	-0.0137***	-0.0118***	-0.00980***	-0.00950***	-0.0124***
	(0.00151)	(0.00176)	(0.00331)	(0.00185)	(0.00181)	(0.00165)	(0.00259)
Observations	117	117	113	117	117	117	117
R-squared	0.847	0.903	0.413	0.883	0.905	0.918	0.788
Districts	25	25	24	25	25	25	25

Notes: Panel of district level measures for six waves of surveys with corresponding contemporaneous disaster data. Models include a constant term, district and time fixed effects. Errors clustered at the district level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Discussion and Conclusion

We explore the impact of natural disasters on income inequality in Sri Lanka at district level, the first study of this nature for the country. We construct a unique panel dataset for the purpose that includes *inter alia* district wise inequality/income measures and percentages of population affected due to natural disasters in each district for the six survey periods of the HIES series between 1990 and 2013. Using panel fixed effects estimator as the main empirical strategy we find that contemporaneous natural disasters and their immediate lags decrease district level income inequality as measured by the Theil index, and substantially so. These results are robust across alternative inequality metrics, sub-samples and alternative estimators. However, we do not find any evidence to the effect that natural disasters affect household expenditure inequality. This is possible if households do not change their expenditure patterns despite their income being affected by disasters or if they might reduce their expenditure proportionately across income quintiles as a result of disaster consequences.

Further analysis suggest that although natural disasters negatively affect household income across all the quintiles, rich quintiles disproportionately bear direct disaster damages at a higher cost. Even though the poor are more vulnerable to disasters, when the poor live a subsistence lifestyle and if they do not possess or own much material assets, their losses will be less compared to the rich. Rich may lose income deriving capital assets more due to destruction and through sale as a coping strategy. On the other hand, if the poor is mainly engaged in low-skilled or unskilled labour they can easily diversify their income sources in the aftermath of a natural disaster. Whilst the rich may suffer profit losses, disasters may open the poor a door for new opportunities. It is evident from our decomposition results that natural disasters decrease non-agricultural income inequality and non-seasonal agricultural income inequality. Household income composition shows that the richest quintile receive a much higher share of their income from these very activities compared to the poor. When the rich suffers greater losses in profits and income due to disasters, it is inevitable that household income inequality would decrease, however, at the expense of the rich.

Our findings warrant policies to take care of the poorer individuals who are more vulnerable to disaster damages and moreover, to safeguard the interests of middle and higher income groups in disaster consequences.

To achieve effective poverty reduction and inclusive growth, the desired is a lower inequality in general. McKay and Pal (2004) present strong evidence that lower initial inequality has a favourable influence on subsequent consumption across many Indian states. Although, lower income inequality is desirable for poverty reduction and to achieve inclusive growth, as a low income inequality derived through higher damages caused to middle and richer quintiles does not reflect true distributive justice, change of inequality in the face of natural disasters should be read with caution. Further, policy makers should give sufficient consideration to natural disasters in designing and implementing policies to promote poverty reduction and inclusive economic growth.

Our study does not capture potential internal migration as a result of natural disasters which would otherwise have explained the decrease in income inequality. This would be a limitation to our analysis. Future research can address this issue although this study is constrained with data availability. Further, Sri Lanka is just one country out of many that face various natural disaster consequences and issues relating to distributive justice at the same time. Furthermore, as Sri Lanka is a lower middle income country with an economy oriented towards services and industry, it could not represent lower income countries which mainly depend on agriculture and are more vulnerable to disasters. Therefore, this analysis could be repeated for other countries with better data as an avenue for future research.

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Appendix

Table A.1: Share of income by component (%)

		Employ	Agri	Agri_other	Non_agri	Kind	Receipts	Total
1990/91	q1	43.28	7.94	6.34	6.55	15.76	20.21	
	q2	48.58	6.49	7.99	9.08	12.30	15.47	
	q3	50.26	6.44	8.79	8.07	11.74	14.70	
	q4	46.39	6.34	9.09	12.56	12.00	13.56	
	q5	34.74	4.67	10.21	25.36	11.98	12.86	
1995/96	q1	46.38	7.42	5.97	1.12	20.78	18.39	
	q2	49.59	6.08	7.63	9.21	15.24	12.37	
	q3	51.42	4.70	7.46	9.93	14.40	12.01	
	q4	48.77	3.90	7.11	12.14	14.76	12.99	
	q5	41.95	2.18	7.95	21.51	14.32	12.29	
2002	q1	71.20	8.71	6.37	-45.57	38.31	21.00	
	q2	52.61	4.19	6.21	9.81	17.35	9.76	
	q3	50.84	3.68	6.66	10.87	16.72	11.30	
	q4	47.58	2.98	6.24	12.84	16.77	13.46	
	q5	35.23	1.82	8.34	22.20	14.13	18.17	
2006/07	q1	45.49	4.59	3.78	-3.32	32.75	16.76	
	q2	45.55	3.03	4.43	10.42	22.88	13.62	
	q3	43.78	2.59	5.17	12.41	19.79	16.19	
	q4	40.23	1.95	6.17	13.99	17.90	19.75	
	q5	28.39	1.36	13.08	20.11	10.40	26.45	
2009/10	q1	46.15	6.13	1.99	-10.47	36.81	19.37	
	q2	43.21	4.26	4.17	10.74	22.64	14.88	
	q3	42.50	3.77	5.06	12.31	20.00	16.48	
	q4	39.75	3.09	5.36	12.53	17.91	21.52	
	q5	22.45	1.75	16.47	28.69	10.08	20.58	
2012/13	q1	42.37	4.10	0.89	-4.84	37.95	19.58	
	q2	43.96	3.12	4.40	11.23	21.70	15.57	
	q3	44.56	2.47	4.54	11.97	19.12	17.35	
	q4	39.90	2.09	5.12	12.97	16.89	23.06	
	q5	26.62	1.26	13.88	20.34	11.03	26.81	
Significant Impact	Dis			↓	↓	↓		**↓**
	Dis_lag1							
	Dis_lag2		↑		↓			**↓**
	Dis_lag3	↓		↓				**↓**
	Dis_lag4				↑		↑	**↑**
	Dis_lag5	↑					↑	